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# Concurrent hierarchical finite state machines for modeling pedestrian behavioral tendencies

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## Abstract

A detailed and realistic simulation of pedestrian behavior requires a precise modeling of human decision making processes regarding action prioritization and selection. This paper presents a novel strategic pedestrian decision making model based on concurrent hierarchical finite state machines. The model is capable to create goal directed behavioral tendencies, which are operational guardrails for tactical models. The decision model is inherently flexible and scalable, being adaptable to different application scenarios, behavioral demands and input parameters. The applicability of the model is shown by means of an example. Furthermore, we discuss a validation and calibration approach for the decision model.

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**Keywords:** concurrent hierarchical finite state machine; cognitive model; strategic pedestrian dynamics model;

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## 1. Introduction

The application of pedestrian simulations ranges from a *pattern of life approach* by Shao and Terzopoulos (2005) up to *investigating tragic incidents* by Alonso-Marroquin et al. (2013). Complex simulation scenarios, that cover a wide spectrum of activities a pedestrian could perform, are especially challenging to model, e.g. festivals with fairground rides and live bands, or train stations. Additionally, activities themselves change over time, stores in shopping centers may be closed or special offers could increase the attraction of a location for some pedestrians. Advanced concepts, like those presented by Silverman et al. (2006), by Orozco et al. (2010) or by Schmidt (2002),

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offer a versatile framework for modeling cognitive decision processes for behavior and activity selection. These models are however not specialized for pedestrian dynamics requirements and thus are difficult to implement, see Park et al. (2003) and Pelechano et al. (2005). Nonetheless, the approach described in Pelechano et al. (2005) is capable of creating the required action selection decisions in a pedestrian dynamics setting. We aim to create a model that will close the gap between such abstract cognitive models and pedestrian simulation demands. As part of this research, this paper presents a cognitive pedestrian decision model (PDM). An application of this model, on top of a pedestrian simulation engine, is able to describe goal directed behavior by selecting objectives, which are alterable due to changes in their underlying properties. As the model is structured as a generic template, it can easily be adapted to different requirements of specific application demands.

For implementing the PDM, an approach based on concurrent hierarchical finite state machines (CHFSM) is applied. Previous works by Joo et al. (2013) and Ming et al. (2010) have shown that the finite state machine (FSM) concepts can be beneficially applied in the context of pedestrian simulation. As a basis for modeling the pedestrian's cognitive processes the hierarchical model of approach-avoidance motivation (HMAAM) by Elliot (2006), a psychological motivation model, is used.

The paper is structured as follows. In Section 2 the model will be categorized according to the behavioral levels of Hoogendoorn and Bovy (2004), and Wijermans (2011). In Section 3 a short overview of the concepts of the approach and avoidance distinction and the HMAAM is presented. The PDM is explained in Section 4. In Section 5, a simple application scenario of the model is outlined. An approach for calibrating and validating the model will be discussed in Section 6.

## 2. Model categorization

Hoogendoorn and Bovy (2004) have introduced a hierarchical approach for modeling pedestrian behavior by providing three modeling levels, namely the strategic (top) level, the tactical (medium) level and the operational (low) level. In a pedestrian simulation engine implementing this approach, the adjacent levels interoperate by data transfer: the higher levels pass input parameters to lower levels and lower levels return processing information to higher levels.

Models of the operational level focus on describing walking behavior, body movement as well as the small distance interaction of pedestrians, e.g. Seitz and Köster (2012) or Park et al. (2013). Tactical models provide a walking path that consists of a set of intermediate targets, thus describing how a location is reached for performing a desired activity. Additionally, tactical models choose the activity area if an activity can be performed at different locations. Models of the tactical layer are often based on routing algorithms, e.g. Höcker et al. (2010), or Geraerts and Overmars (2007), but also on non-graph concepts, such as the application of the floor-field method by Hartmann (2010). The purpose of a model of the strategic layer is to prioritize a set of activities over another set. Different researchers have developed models for the strategic level, e.g. Wijermans (2011) or Shao and Terzopoulos (2005).

The PDM presented in this paper operates on the strategic level. Objectives are provided by means of a set of behavioral tendencies. A behavioral tendency is a triple, consisting of a tactic, a priority, and an activity. The underlying tactical model must also be able to process the behavioral tendencies. The behavioral characteristics of the pedestrians for a given scenario, including specific activities and objectives, can be defined in a flexible manner.

An alternative approach to describing the structure of pedestrian behavior was introduced by Wijermans (2011). The approach is called the multilevel concept and is based on crowd psychology research. It describes a link between observable group patterns, visible individual behavior, and internal cognition processes with a strong focus on the individual level, see Fig. 1.

Three different levels are defined: the group level (inter-individual), behavior level (individual) and cognitive level (intra-individual) level. On the group level, the visible patterns of a crowd of people emerge, resulting from the subsumed individual behavior of nearby pedestrians. While this view opposes the concept of a group-mind it does not omit social concepts like leadership (Wijermans, 2011). On the individual level, the behavior of an individual pedestrian can be observed. The group level influences the individual behavior, e.g. by physical restrictions or social

interaction. On the cognitive level, decision making is performed. Similarly to the group-individual linkage, decisions change the observable behavior of an individual, e.g. a pedestrian starts to walk to a location without a noticeable cause. As conclusion follows, that internal decision making and external social and physical influences give rise to the observable individual behavior of a pedestrian. We make use of this concept for categorizing the PDM. From the multilevel point of view, the PDM operates on the cognitive level because it describes decision making processes.

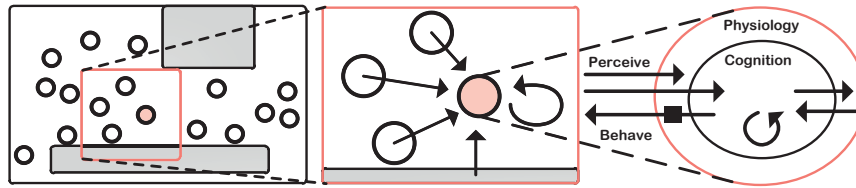


Fig. 1. (Recreated from Wijermans (2011)) Visualization of the link between the group level (left), the behavior level (middle), and the cognitive (right) level. The directed arcs in individual level represent the influences on the individual from the cognition and group level.

### 3. Approach and avoidance motivation as theoretical background

The pedestrian's cognitive model as proposed in this paper is constructed by utilizing the hierarchical model of approach and avoidance motivation, as defined by Elliot (2006). The HMAAM is based on the concept of approach and avoidance distinction. This distinction helps to explain and predict motivated behavior, elucidated by Elliot (2006), and Elliot and Covington (2001). Referring to Elliot (2006), a shortened definition for the distinction is: *approach motivation is the direction of behavior towards positive stimuli and avoidance motivation is the direction of behavior away from negative stimuli*. Following Elliot (2006), five additional aspects have to be considered:

- Approach and avoidance include motivation and goal pursuing, thus vitalize and guide behavior.
- Approach and avoidance include physical or psychological movement. Positive stimuli should be kept near and negative stimuli should be kept away of the organism.
- Approach and avoidance motivation explains preventing negative and acquiring positive stimuli but also the maintenance of existing states.
- Positive and negative do change their meaning in different contexts.
- Stimuli represent real and internal-generated objects, events and possibilities.

The outlined distinction is the vital basis for the HMAAM. Goals play a central role in the HMAAM because they guide behavior towards or away from an object. Thus goals are described as a directional function of behavior (goal pursuing) but not its energization function (motivation), hence being insufficient for establishing behavior. A main assumption of the HMAAM is that a goal and the underlying motivation are separate entities but hierarchically linked. Motivations change the characteristics of goal pursuance, which in turn changes the behavioral pattern. The same goal can be pursued by different motivations and the same motivation can serve for pursuing different goals.

Some pedestrian dynamics models, e.g. the social force model by Helbing et al. (2002), use the concept of approach and avoidance distinction intuitively. Pedestrians approach a given goal location and avoid other pedestrians and walls. A motivation for walking to a location can be given by the application of the model, e.g. in an egress scenario, saving one's life. In general, objects a pedestrian can perceive or knows about may be the origin of an approach or avoidance behavior. This fundamental distinction between approach and avoidance motivation is used as the foundation for modeling the PDM. By adapting the concepts of the HMAAM by Elliot (2006) the cognitive model was developed.

#### 4. Implementation of the pedestrian decision model by concurrent hierarchical finite state machines

##### 4.1. Concurrent hierarchical finite State machines as modeling technique

The concept of CHFSMs, which were developed from FSM by Moore (1956) and popularized by Harel (1987), is an efficient method for modeling reactive systems and a standard approach in software engineering, see Rumbaugh et al. (2004). Applications in robotics show the massive potential of this method, e. g. by Risler (2009) and Loetzsch et al. (2006). Risler (2009) developed a CHFSM framework for modeling the behavior of autonomous agents. This framework, the *Extensible Agent Behavior Specification Language* (XABSL), see also Loetzsch et al. (2006), is based on deterministic Moore automata and we use it for modeling the CHFSM based PDM.

A FSM consists of a finite set of states. If a state is active, an adjacent state can be activated if the transition between both states is activated. By activating a state, output data can be written, and the previously activated state is deactivated. In a hierarchical finite state machine (HFSM), each state itself can consist of a FSM, thus activating a state also activates a FSM. An important concept of HFSM is that, if a state with activated child states is deactivated, all child states are also deactivated. In CHFSMs a state can comprise of a finite set of concurrent FSMs. Fig. 2 presents a showcase CHFSM with a state activation tree and an example state transition. During the modeling process of machines of the PDM a subsequent refinement was intended, which follows the approach of Risler (2009).

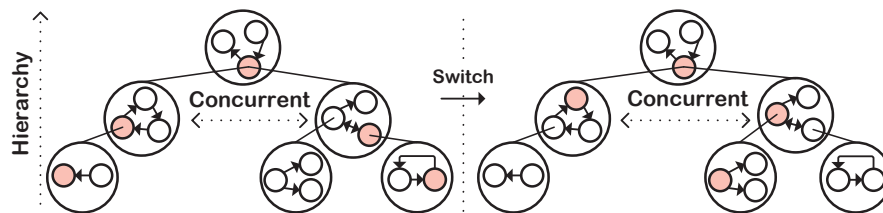


Fig. 2. Showcase CHFSM. States and FSMs are visualized as a circle and the activation tree is built by the highlighted states and undirected arcs.

##### 4.2. Model overview

The developed PDM is modeled by CHFSMs, by an interface to a tactical model and by trigger functions (TFs), which serve as data input provider for the CHFSMs. The fine interplay of different *motivation*, *pursuance* and *process* machines, by event generation and consumption, models the cognitive decision making process of a pedestrian. These machines are subsumed in a *goal* CHFSM. The schematic overview of the model is given in Fig. 3 a) and Fig. 3 b) describes the overall information flow in the PDM.

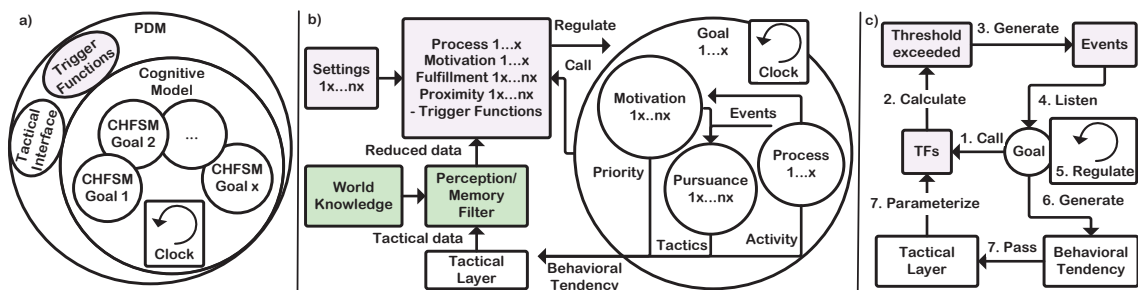


Fig. 3. a) The schematic view of the PDM. b) The view of a CHFSM for a goal. c) The cognitive process cycle

In order to implement the HMAAM, two coexisting CHFSMs are necessary. One machine handles motivation and another handles goal pursuance. Because the motivation influences the fashion of goal pursuance, a goal CHFSMs contains motivation and pursuance CHFSMs. A process describes an ordered set of activities, e.g. the process to get ready to ride a train consists of the activities buying a ticket, going to the platform, walking to the waiting location and entering the train. Each activity represents a sub-goal, which needs to be fulfilled to complete a process. A process FSM, which consists of a set of activity states, is a mandatory part of a goal, because it defines the order of the pursued activities. The fashion of how an activity is pursued differs between activities, thus each activity is connected to its own pursuance and motivation CHFSM. Each activity is associated to at least one object of the scenario, e.g. in a railway building multiple ticket offices exists, so an activity can be pursued at different locations. Pedestrians execute goals simultaneously, e.g. staying close to friends and going to the platform. This implies that the PDM contains a set of goal CHFSMs, see Fig. 3 a). For details of the motivation, pursuance and process linkage see Fig. 3 b).

The cognitive model is connected to a set of TFs and to a tactical model. The TFs provide input data for the cognitive model, thus induce and regulate the cognitive decision making process. Four types of TFs are defined: the Motivation TF, the Proximity TF, the Fulfillment TF and the Process TF. The detailed purpose of each trigger function is described in Tab. 1. A goal CHFSM generates a behavioral tendency as tactical model input. The processing information of the tactical model is fed back as input to the trigger functions, thus providing spatial and temporal data of a specific approached or avoided objective, e.g. the distance of a pedestrian to the selected goal locations. The data that is fed back enables the TFs to react to tactical decisions. It is important to state that before each knowledge transfer to a TF a perception and memory filter is interposed. The task of these filters is to reduce the world knowledge data set to the pedestrian's data set, similar to the explanations given by Schmidt (2002).

The TFs are also parameterized by predefined pedestrian and goal information. These settings consist of static information, e.g. the gender of a pedestrian, a fixed group affiliation, the point of time a train will arrive or the amount of time an activity consumes during processing. Additionally, each pedestrian possesses dynamic goal dependent characteristics, e.g. the pedestrian's preferred waiting distance to a rail track. Based on the structure and interfaces described, the cognitive process cycle for a goal of a pedestrian can be described as given in Fig. 3. c).

Table 1. Trigger Functions

TF Name	Purpose	Generated events	Calling state
Motivation	Calculates how motivated a pedestrian is to pursue a goal. The influence on the motivation can range from personal preferences to specific time dependent goal attributes, e.g. a happy hour.	Lessen, Seek	<i>CheckMotivation</i>
Proximity	Calculates if a pedestrian reaches a goal. The influence on the proximity can vary from personal preferences to fixed distances, e.g. to buy a ticket the pedestrian has to stay very close to the ticket office.	Emerging, Reaching	<i>CheckMotivation</i>
Fulfillment	Calculates if an activity is finished. Influences are often time dependent, e.g. how long it takes to buy a ticket or if a shop closes.	Abandoned, Achieved	<i>CheckActivation</i>
Process	Calculates if a goal is relevant for a pedestrian, thus if the pedestrian considers a goal or if the location of the next activity is known.	Unknown, Known, Exists, Non-Existent	<i>Process</i>

#### 4.3. Cognitive process by fine interplay of states, events and trigger functions

As stated above, each goal CHFSM consists of motivation CHFSMs, pursuance CHFSMs and a process CHFSM. The CHFSMs listen to specific events and, based on occurring events, state transitions are executed. The fine-grained structure of the CHFSMs is presented in Fig. 4. The name on a directed arc in Fig. 4 is the event or Boolean event expression, which is listened to in order to execute the arc's state transition. Events are generated by calling TFs and by active states whose names exist as a transition label. In Fig. 5 a) a generic and an example version of the event cause and effect chain is presented.

A behavioral tendency for a *goal* consists of a priority, tactic and activity. The content of a triple is set by specific active states. The priority value equals a sub-state of a *prioritization* FSM. The *prioritization* machine reacts on an increase or decrease of the level of the Motivation TF and secures the results in three levels of prioritizations: *low*, *middle* and *high*. It is possible to create a more fine-grained distinction by introducing more intermediate states of priority. The tactic value of the tendency equals a sub-state of the *wayfinding* or *reached* FSM. Two fundamental wayfinding concepts, searching and routing, are taken into account for realizing the navigation to an object, the location of which is either known or unknown (Allen, 1999). As stated above, a pedestrian shall maintain an approach or avoidance state by physically staying close to, or away from an object. If a pedestrian is far away from or close to a goal location the *keep reached* state of the *reached* FSM is set as the tactic value. Additionally, *postpone* states are introduced. If the *prioritization* of a goal is *low*, no behavior is executed, indicated by an activated *postpone* state. The activity value of the tendency equals the current *activity* state of the goal's *process*. An example activation tree, which creates a behavioral tendency, is presented in Fig. 5 b). Added together: the tactic defines how to pursue a goal, an activity defines where the behavior is executed, and the priority of the activity determines its importance.

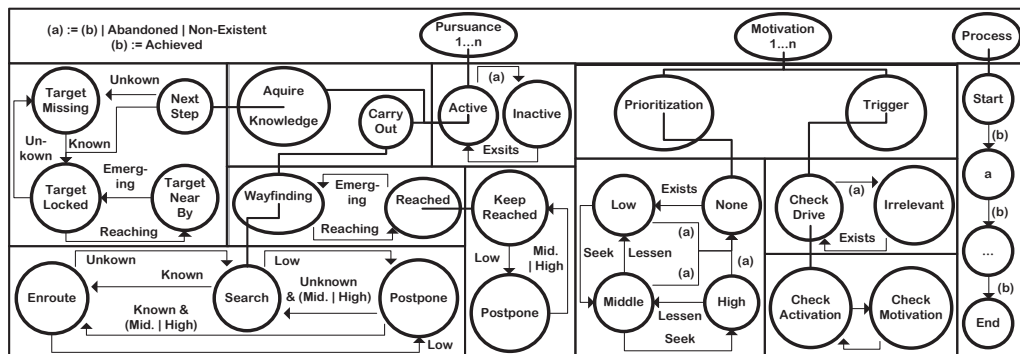


Fig. 4: Fine grand view on a CHFSM for a *goal*. Each cycle is a state or FSM. The origin of an undirected arc is a parent FSM. A state is a start state if connected to an undirected arc. Directed arcs are state transitions and directed arcs without a label automatically switch each clock pulse.

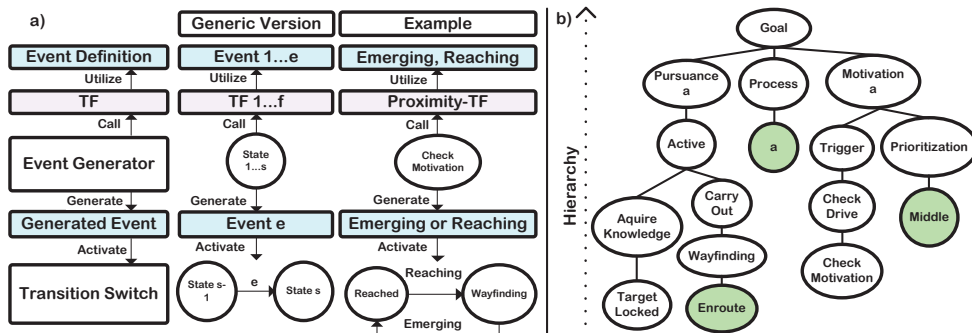


Fig. 5. a) The event cause and effect chain. b) An activation tree, with the behavioral tendency being highlighted.

## 5. Example Application

We implemented the PDM in a pedestrian simulator. For a proof of concept we applied the PDM to a student career fair scenario, which we surveyed with cameras. Different strategic behavior patterns were observed in this



example. As shown in Fig. 6 a) the activities *listen to lecture E*, *visit a booth left/right B/C*, and *walk away left/right A/D*. Additionally a *stay in your group X* activity was added, because visitors often walked together.

For simplification, each process consists of only one activity, thus six approach goals exist. The spatial layout, see Fig. 6 b), was simplified, but the observed places of interest and their spatial properties are still present. The simplification is legitimate, as we not interested in local pedestrian interaction phenomena, but aim highlight the overall group behavior patterns. The PDM was calibrated by data from a video capture of 16 minutes. We manually collected the arrival, leave and dwell time, for *B*, *C* and *E*, and the ingress and egress frequency for *A* and *D*. The data provided the information that 635 pedestrians crossed the area, 28% listened to the lecture in average for 3'28'', 62% exited by *A*, 26% exited by *D*, 1.4% visited *C* in average for 0'28'' and 1.5% visited *B* in average for 4'29''. The lecture starts at second 50 and ends at second 955. Fig. 6 c) presents arrival and leave data collection for activity *E*. The size of a group of pedestrians ranges from 1 to 4, based on the data provided by Peters and Ennis (2009).

The PDM operates on the strategic level, thus a simple tactical model was applied. The model is able to handle multiple behavioral tendencies of the same prioritization by the use of three rules: the *X* activity is preferred over other activities, the activity with the shortest distance to a pedestrian will be selected, and a person waits if she/he reaches a selected goal. As operational model, the social-force model by Helbing et al. (2002) was applied. The social force model was implemented with 1.34 m/s standard velocity (Weidmann, 1993) and a lowered force between pedestrians was assumed due to the less stressed situation at a student career fair. We used sigmoid functions for the Motivation TFs, similar to Wijermans (2011) or Schmidt (2002), and linear functions for the Proximity TFs and Fulfillment TFs. Threshold values and parameter of the TFs were deducted from the frequency and duration a goal was visited.

The time step for the social force model is set to 100ms. The simulation runs 16 minutes. The PDM switches every 500ms for each pedestrian. In Fig. 7, examples of the generated behavioral pattern are presented.

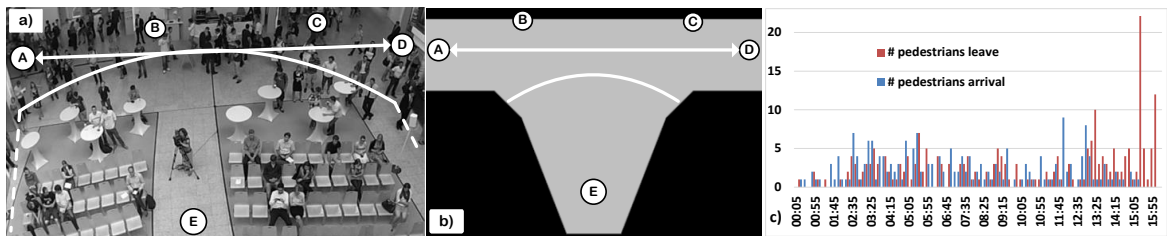


Fig. 6. a) The career fair scenario. b) The simplified layout of the scenario. c) A sample of manually collected data of activity *E* c).

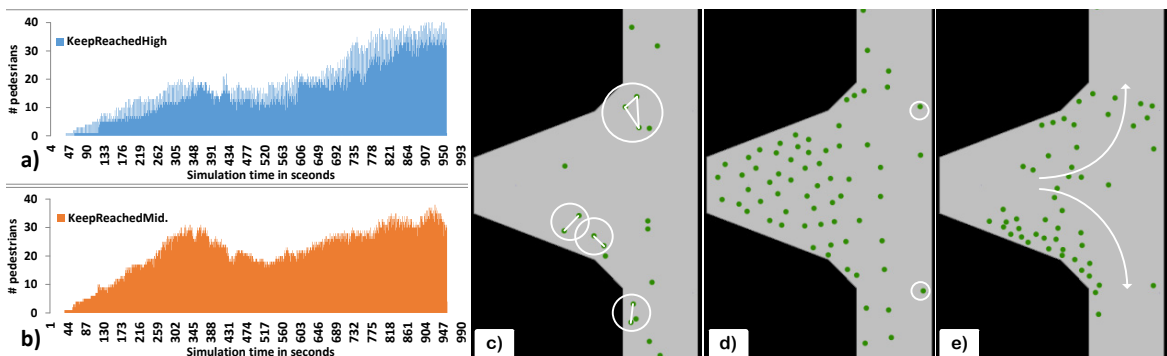


Fig. 7. a) and b) histograms show the number of keep reached tactic activated for *E*. The simulation at run time c) 83, d) 791, and e) 965 in seconds are shown. c) Groups are highlighted. b) Visitors of the stand *B* and *C* are indicated. e) The self-driven egress after the lecture ends.

## 6. Calibration and Validation Discussion

In order to validate the result pattern of the goal directed behavior and to calibrate the model, a comprehensive measuring of the observable temporal spatial parameters is mandatory. The core concept is to track the pedestrians and translate their trajectories into a distribution, but tracking by hand is a tedious and prolonged process. The PDM benefits most from the methodology of automatically tracking pedestrians without markers for non-laboratory conditions, as presented by Rodriguez et al. (2011), or Ali and Dailey (2009). A trajectory map (TM) can be created by tracking most of the pedestrians in a scenario. A TM is similar to a pedestrian behavior map, see Borrmann et al. (2011). Based on a TM, origins of goals can be extracted by hand, for two extraction examples see Fig. 8. For approach goals the extraction is easier than for avoidance goals, e.g. if a pedestrian avoids dogs this could not be easily identified. This approach follows the multilevel concept introduced in Section 2. The group level pattern can be extracted by observing the individual level. By extracting the typical distance and frequency of pedestrians for the origins the TFs parameter, can be deduced.

For validation purposes, the TM and the time dependent distribution of the behavioral tendencies of a simulation are compared. The distance of the pedestrians to a specific goal origin should be equal to the distance for which the keep reached tactic is activated. A well calibrated pedestrian decision model should draw the same number of pedestrians to or away from an area for a specific duration. A challenge for this approach are activities which are not spatially fixed, e.g. staying in your social group. In order to validate these dynamic data, a TM needs to be extended with data of moving goals.

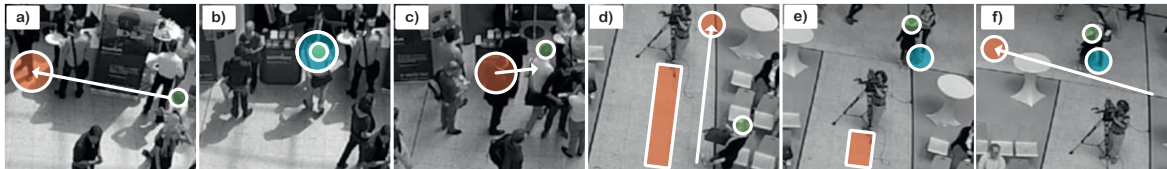


Fig. 8. An approach goal a)-c): a) the pedestrian approaches a stand, b) the distance to the stand is stable within a spatial boundary, and c) After a specific duration the pedestrian increases the distance again. An avoidance and two approach goals d)-f). d) The pedestrian does not cross the camera's line of sight, e) meets up with a friend, and f) they exit the area together.

## 4. Conclusion

In this paper we presented a pedestrian dynamics model, which operates on the strategic level. It is implemented by CHFSMs and based on the HMAAM. From a multilevel point of view, a cognitive model was developed. The model was designed as a generic template in order to enable reusability for different pedestrian dynamics applications. It was created in order to overcome the research gap between over-simplified models, which fail to create authentic pedestrian behavior in complex settings, and high-level cognitive models, which cannot easily be applied in pedestrian dynamics. As proof of concept, the PDM was applied to model pedestrian behavior at a career fair scenario. The CHFSM modeling approach has proved itself as an outstanding method for modeling complex pedestrian behavior concepts, because we were able to model pedestrian decision processes by the fine interplay of the components of the presented CHFSMs.

The core of calibration of the PDM is to extract TF parameters from video. A TM needs to be generated in a spatial temporal metrics fashion by capturing the distance and the duration of pedestrians to all goals. The data is translated into a calibration distribution. For validation, the behavioral tendencies of a simulation need to be captured and compared to the TM.

In further research we aim to present an in-depth description of the validation and calibration concept of the PDM, which is also applicable to other strategic models. In addition, an elaborated PDM is targeted by refinement of the CHFSM, and by presenting a set of predefined goals and corresponding TFs.



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